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A Note on U.S. Worker Turnover ^{*}

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Abstract

The length of new employment relationships is of first order importance for a number of questions in recent macro-labor research. We investigate it using data from the Survey of Income and Program Participation for the U.S. from 1996 onwards, and document that above two-fifths of newly employed workers fall into non-employment within a year. We also find that the transition rate from employment to non-employment within the first year varies significantly for different groups of the population, increases with the duration of the previous non-employment spell, exhibits an acyclical or weakly procyclical pattern and a much higher volatility than the unemployment rate.

Keywords: Worker turnover, non-employment duration, cyclicity, volatility

JEL Codes: J31, J60, J63

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1 Introduction

Most models of the labor market assume that exit rates from employment are constant in job tenure and equal across all workers.¹ Although this assumption may be a roughly good approximation once some threshold in tenure has been crossed, it may not be appropriate for a number of questions in the macroeconomic research for which the surviving probability of new matches is central. For example, on the positive side, [Pries \(2004\)](#) presents a theory that reconciles the strong persistence of the unemployment rate with the high exit rates from unemployment by modelling jobs as experience goods and laid-off workers engaging in a series of short employment spells. [Pries and Rogerson \(2005\)](#) study to what extent the large differences in worker turnover between the U.S. and European countries can be accounted for by policy differences, and be reconciled with similar job turnover rates. On the normative side, [Choi and Fernández-Blanco \(2015\)](#) show that the optimal design of the unemployment insurance and, more generally, the government intervention is affected by how sizable both present and future unemployment risks are. This note aims to shed light on the exit rates from employment of newly employed workers in the U.S.

Using data from the Survey of Income and Program Participation (SIPP) from 1996 onwards, we document that over 40% of newly employed workers return to non-employment within a year, whereas this annual transition rate drops to 24% in the second year. Our estimates are comparable to the two older references we are aware of. [Farber \(1999\)](#) estimates these transition rates at 50% and 33%, respectively, using the National Longitudinal Survey of Youth (NLSY). [Anderson and Meyer \(1994\)](#) finds that the quarterly permanent separation rate amounts to 34% and 12% for a job tenure of 6 and 18 months, respectively, using firm-worker data from the Continuous Wage and Benefit History (CWBH). Furthermore, we find that approximately 20% of our sample comprises individuals with several transitions to non-employment, which shifts the aggregate statistic upwards.

Furthermore, we find that the transition probability in the first year after reemployment is larger for lower-educated and younger workers, whereas there is no significant differences by gender. In line with the micro labor literature, we show that the transition rates steadily increase with the length of the previous non-employment spell. Although this positive relationship points to the true effect of previous non-employment experiences on future new occurrences, as analyzed e.g. in [Heckman and Borjas \(1980\)](#) and [Arulampalam et al. \(2000\)](#), this analysis is beyond the scope of this note.

We also find that starting wages of those workers who stay employed one year later

¹See [Rogerson and Shimer \(2010\)](#).

are 14% higher than those of the individuals who fall into non-employment. As mentioned above, the large worker turnover rate in the U.S. has been usually modeled interpreting match quality as an experience good since Jovanovic (1979). This wage difference suggests, instead, that learning about match quality is probably not a complete account for these high separation rates. Finally, we study the cyclical properties of these transition rates to non-employment. We find that it is much more volatile than and not (or weakly negatively) correlated with the unemployment rate. We observe no sizable differences in this regard over time, including the great recession.

In Section 2, we describe the data set and our assumptions. Then, Section 3 shows the results. Finally, we summarize our findings in the conclusion section.

2 Data

The SIPP allows us to study long employment histories at high frequency (weekly) level. In what follows, we use the 1996 and 2001 panels, containing labor force histories observed between 1996 and 2003, except for the business cycle analysis for which we will also use data from the 2004 and 2008 panels.² A panel in the SIPP is formed by a number of interviews, called waves. The first panel is formed by 12 waves and the second by 9, covering approximately 4 and 3 years, respectively. Individuals are interviewed retrospectively every four months. In particular, they are asked to report their employment status for each week of the previous four month period, their wages, hours of work and job id number if employed. We label a worker as employed (E) in a given week if he reports to have a job, regardless of whether he is working, absent or on temporary layoff, worked as a paid employee or in his own business.³ Everyone else is labeled as non-employed (\bar{E}).

The distinction between non-employment and unemployment is somewhat ambiguous, particularly when analyzing transitions to and from employment. The Bureau of Labor Statistics considers an individual as unemployed if he or she does not have a job at the interview time and is actively looking for one. The remaining non-employed workers are cast into the category of not-in-the-labor-force (NILF). Using Current Population Survey (CPS) data for the 1967-2012 period, Elsby et al. (2013) document that transitions in and out of the

²The covered time periods are: February of 1996 to February of 1999; December of 2000 to December of 2002; January of 2004 to December 2006; August of 2008 to July 2012. Although we exclude the 2004-2012 period from our sample in most of the analysis to avoid the years around the great recession and previous expansion, we find no major differences when extending the dataset to 2012 as reported later.

³As pointed out in the SIPP technical documentation, this is an important difference with respect to the CPS because the employment category in the latter does not include “those temporarily absent from a job because of layoff and those waiting to begin a new job in 30 days”.

labor force are frequent. In particular, the monthly transition rate from unemployment to NILF is above 20%, only five percentage points lower than the transition rate to employment. Likewise, transitions out of employment are equally divided into unemployment and NILF. Jones and Riddell (1999) highlight the heterogeneity present within these last two groups, and split the NILF category into two subgroups depending on labor market attachment. Workers are referred to as *marginally attached* if not searching but reporting that they want a job. Using Canadian data, they find that marginally attached workers find jobs at the same rate as the unemployed who either only used a public employment agency or looked at advertisements, and at a rate four times higher than the remaining NILF individuals. Building upon this research, Krusell et al. (2011) redefine the unemployment pool to incorporate the marginally attached workers.

Our data work has a similar spirit. We restrict our sample to individuals aged 16 to 65 who lose and subsequently find a job within the period spanned by the survey. By focusing on $E\cancel{E}E$ spells, we define *attachment* to the labor market as being employed at least twice within the panel time window. An employment to non-employment ($E\cancel{E}$) transition occurs when an employed worker finds himself with no job for at least one week. Similarly, a $\cancel{E}E$ transition occurs when a non-employed worker has a job for at least one week. We do not interpret $E\cancel{E}$ spells shorter or equal than 2 weeks as separations if the job id remains unchanged. It can be argued that a number of $E\cancel{E}E$ observations with a very short \cancel{E} spell mask job-to-job transitions. However, according to our definition of employment, we label those workers with a job but absent from work as employed. Furthermore, we only consider spells with a positive number of working hours reported at reemployment. Importantly, since we aim to evaluate the turnover within the first year, we only consider individuals whose employment histories are observable for at least a year after reemployment.⁴ Our sample consists of 16616 $E\cancel{E}E$ observations and 13270 individuals. An individual stays in our sample for 40.7 months on average, and for at least 15 months. Table 1 shows that 80% of the spells in our sample correspond to workers who appear only once.

3 Results

In this section, we first report empirical estimates of the transition rate into non-employment within a year after reemployment, to which we refer as the $E\cancel{E}$ rate for readiness. Then, we document its dynamics over the length of the previous non-employment spell as well as its

⁴Arguably, our estimate of the turnover rate is likely to be conservative because of potential attrition bias.

$E\bar{E}E$ spells in sample per individual	Freq.	Percent
1	10545	79.46
2	2223	16.75
3	404	3.04
4	85	0.64
5	7	0.05
6	4	0.03
7	2	0.01
Total	13270	100.00

Table 1: Number of Observations per Individual

Note: Data are from the 1996 and 2001 SIPP panels. *Freq* refers to the number of observations of a given category.

cyclical. We also find a significant wage difference between workers who stay employed during the first year and those who do not.

3.1 $E\bar{E}$ Transition Rates

We find that the $E\bar{E}$ rate amounts to 42.80%.⁵ We refer to the workers who transit to non-employment within a year as *non-stayers*, and as *stayers* to those who stay employed longer than one year. Furthermore, 28.45% of new employment spells, conditional on the worker being in the sample for at least half a year after reemployment, end in non-employment within the first six months. In contrast, the $E\bar{E}$ transition rate within the second year of employment, conditional on being a stayer and remaining in the sample for at least two years since reemployment, is 24.11%. Figure 1 shows this declining pattern of the quarterly empirical exit rates from employment by gender and education, conditional on staying employed at least until the previous quarter and in the sample at least until that quarter. We observe no big differences across genders, but a striking higher separation rate for lower educated individuals.

For comparison, Farber (1999) reports that one third of new full-time jobs end in the first six months, one half in the first year, and two thirds within the first two years. His last estimate becomes one third when conditioning for staying employed at the end of the first year. Therefore, his numbers are reasonably close to ours despite the differences in the datasets.⁶ Using unemployment insurance data from CWB for the 1978-1984 period, Anderson and Meyer (1994) estimate the quarterly permanent separation rate for workers

⁵The figures for the 1996, 2001, 2004 and 2008 panels are 43.93, 40.62, 43.83, and 40.78, respectively.

⁶Farber (1999) considers full time jobs and uses NLSY data. The discrepancy between SIPP and NLSY estimates is mostly because younger workers (oversampled in the NLSY) are more likely to experience job terminations.

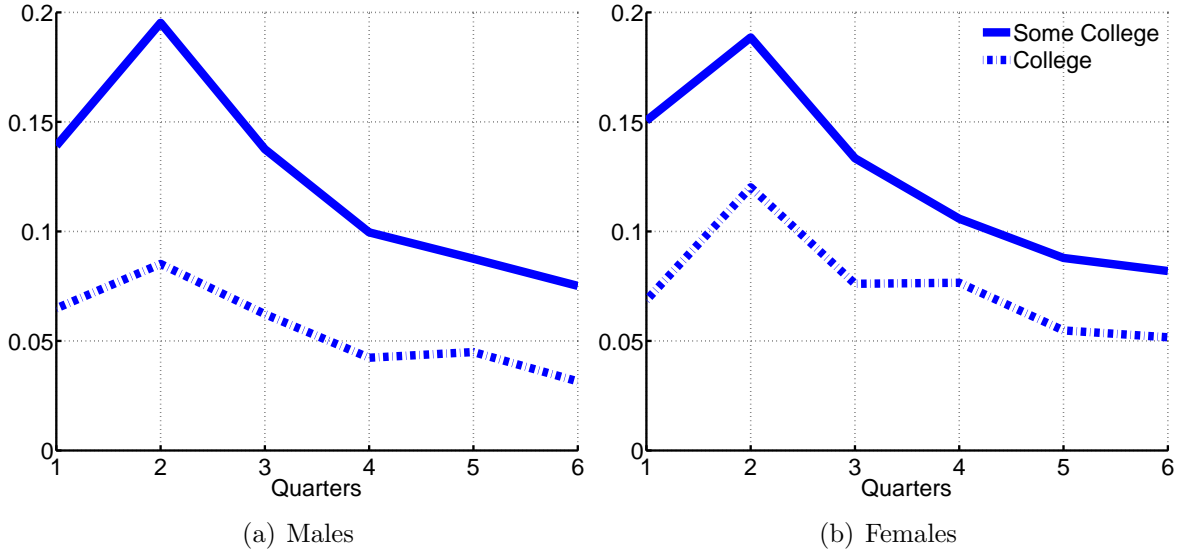


Figure 1: Quarterly empirical exit rates from employment by gender and education.

Note: The data are from the 1996 and 2001 SIPP panels for all workers. The *College* label refers to individuals with college or post-college education, and all other individuals are cast into the category of *Some College*. The statistic at q quarters refers to the empirical exit rate for individuals who have been employed for at least the first $q - 1$ quarters since reemployment and stay in the sample for at least one more quarter.

with job tenure below one year at 30.53%, over four times larger than for the remaining workers. Certainly, there is a sharp contrast in $E\bar{E}$ transition rates between the U.S. and most European countries, which may be explained by differences in employment protection legislation. For example, using West Germany panel data, [Wolff \(2004\)](#) estimates the match-destruction rate at the end of the first year at 23%.

Table 2 shows that non-stayers differ from stayers along many dimensions: Stayers are not only more educated, but also are older, work at bigger firms,⁷ and work more hours on average. They also earn significantly higher wages, even if restricting the sample to college and post-college graduates. Stayers also have shorter non-employment spells prior to reemployment.

The estimate of the $E\bar{E}$ transition rate is sensitive to a number of factors. First, as Table 2 suggests, age appears to be a key characteristic. If we restrict our sample to individuals aged 20 to 60 instead, the transition rate within the first year after reemployment falls to 37.87%. Rates remain high for most age groups. For example, the transition rate for prime-age workers (30 to 45 years old) is 34.45%.

⁷The average firm size for each subgroup is not reported in Table 2 because the SIPP measure of firm size is piecewise, taking value 1 if fewer than 25 employees, 2 if between 25 and 99, and 3 if over 100 workers. The average firm size in the worker's location is 1.78 for non-stayers and 1.90 for stayers.

Variable	Non-stayers		Stayers	
	Average	St. dev.	Average	St. dev.
(log) Hourly wage	1.758	0.785	2.068	0.756
Age	28.883	11.984	33.791	12.077
Female	0.544	.498	0.537	0.499
White	0.828	0.377	0.834	0.372
Black	0.125	0.331	0.115	0.319
Married	0.320	0.466	0.476	0.499
College	0.085	0.279	0.161	0.367
Post-college	0.022	0.146	0.062	0.242
Non-emp. duration	19.968	18.657	17.049	16.749
Hours of work	31.370	13.562	35.304	12.803

Table 2: Descriptive Statics.

Note: The data are from the 1996 and 2001 SIPP panels. *Non-stayers* are workers who experience non-employment within one year of becoming employed *Stayers* are those who remain employed for at least one year.

Second, one could argue that the high $E\cancel{E}$ rates reflect the existence of workers who experience several spells of non-employment in our sample. We can further restrict our sample in two ways to examine this point. First, if we only consider the first $E\cancel{E}E$ observation of any individual in the sample, the $E\cancel{E}$ rate amounts to 40.63. If we restrict the analysis to individuals with only one (at most two) observation in the sample, 27.96% (38.51) of them are non-stayers. Although this last figure is still very high, the gap between this number and the $E\cancel{E}$ rate for the whole sample indicates that a subgroup of workers are trapped in $E\cancel{E}E$ cycles, and account for about one fourth of the $E\cancel{E}$ transition rate.

Third, similar to [Fujita and Moscarini \(2013\)](#), we find *seam effects*. That is, although $E\cancel{E}$ rates should not significantly differ for new employment spells starting either at the very first or the very last month of a wave from the other spells, we find that it does as reported in Table 3. This may be read as a form of measurement error.

	Observations	$E\cancel{E}$ transition rate
Overall	7111	42.80
Individuals with a single observation	2948	27.96
Individuals with at most two observations	5773	38.51
E spell starting last month of a wave	1493	47.76
E spell starting first month of a wave	2611	37.85
Recall	1332	36.14
No recall	5779	44.69

Table 3: $E\cancel{E}$ transition rate

Note: Data are from the 1996 and 2001 SIPP panels.

Fourth, jobless workers may be called back by a former employer, an event usually known as a “recall”. When studying the 1996 and 2001 panels, [Fujita and Moscarini \(2013\)](#) have 12245 $E\bar{E}E$ observations. Out of these, approximately 20% result from a recall. This number raises to 32% after an imputation process. SIPP provides a unique job number to identify an employer, with a maximum of two per wave. We identify a recall for a given $E\bar{E}E$ spell if either job id in the first employment spell coincides with either job id in the second spell. We find that recall accounts for 22.18% of the observations, and the observations not-involving a recall amount to 12930. [Table 3](#) shows that these transition rates are lower if a recall takes place.

Fifth, the fraction of non-stayers may be concentrated in a few industries and/or occupations, with a relative high rate of seasonal jobs.

To further control for all these issues, we estimate a Probit regression with a dummy variable which values 1 if the worker is a stayer and 0 otherwise as the dependent variable. We use the national unemployment rate as a business cycle indicator, and monthly dummies to capture seasonality effects. In addition, we control for a number of observable worker characteristics. [Table 4](#) reports the Probit estimates. A large number of these variables are statistically significant, and are in good agreement with the descriptive statistics of [Table 2](#). For example, males and married as well as older workers with high education are more likely to stay employed during the first year after reemployment. The seam dummy is also significant. Remarkably, the unemployment rate is not statistically significant, whereas the estimate of the length of the previous non-employment spell is significant and negative. The predicted $E\bar{E}$ rate when restricting the Probit regression to observations not involving a recall equals 44.22%, which does not differ significantly from the empirical statistic reported in [Table 3](#).

3.2 Duration Dependence in $E\bar{E}$ Rates

The average non-employment duration between the two employment spells for the subsample of observations not involving a recall is 21.17 weeks, and about 72% of these workers find jobs within the first 6 months. The average non-employment duration is much larger than the usually reported estimates mainly because our sample includes the marginally attached workers and excludes recalled workers. Without excluding the rehired workers, the average non-employment duration is 18.30 weeks.

Next, we investigate the relationship suggested in [Table 4](#) between the probability of transiting back into non-employment within a year and the length of the previous non-employment spell. We first compute the empirical $E\bar{E}$ transition rates at each length (mea-

	Stayer Probability	Log Wage
Stayer Dummy		0.132 (0.000)
Age	0.075 (0.000)	0.030 (0.000)
Age squared	-0.001 (0.000)	-0.000 (0.000)
Male dummy	0.105 (0.000)	0.144 (0.000)
Marriage dummy	0.130 (0.000)	0.027 (0.083)
College dummy	0.163 (0.000)	0.243 (0.000)
Post-college dummy	0.237 (0.002)	0.484 (0.000)
(log) Unemp. rate	0.083 (0.563)	-0.220 (0.003)
(log) Non-emp. duration	-0.086 (0.000)	-0.021 (0.002)
Wave start (seam) dummy	0.129 (0.000)	0.054 (0.000)
Observations	12930	11960

Table 4: First Year Separation Rate and Starting Wages

Note: Data are from the 1996 and 2001 SIPP panels for non-recalled workers. P-values are in parenthesis. The first column corresponds to a Probit regression to estimate the probability of staying employed during the first year after reemployment. The second column is an OLS regression with the log hourly wage as the dependent variable. In addition to the reported variables, the set of regressors comprises monthly dummies, a year linear variable, average accumulated unemployment benefits (deflated using the national CPI) and its square, and a number of dummy variables for white race, black race, education, major occupation and industry groups, firm size, and U.S. state as well as seam-month dummies. We use the SIPP longitudinal weights (wpinwgt).

sured in weeks) of the last non-employment spell. In Figure 2, we use dots to plot the empirical rates for observations not involving a recall. It shows that these transition rates systematically increase with the previous duration, particularly for $E\bar{E}$ spells longer than 9 months.

This positive relationship can be affected by the reasons pointed out above. Therefore, we use the same Probit specification now with a quartic polynomial of the length of the previous non-employment spell, and evaluate all regressors at their sample mean, and the non-employment duration at the number of weeks in question. Figure 2 also depicts the dynamics of the $E\bar{E}$ predicted probabilities (solid line) over non-employment duration as well as the 95% confidence interval. Again, there is a positive relationship between the $E\bar{E}$ transition rate and the duration of the previous non-employment spell. In particular, the probit-predicted transition rate is 18% higher for those workers who became employed after half a year, and 31% for those who waited a full year of non-employment, relative to those with a one-week $E\bar{E}$ spell.

Figure 3 shows this relationship for two subgroups of workers depending on whether they experience one or several transitions to non-employment within the sample period. By construction, the $E\bar{E}$ transition rates must be quite higher in the subgroup of individuals with more than one separation as the panel length is between 3 and 4 years. Interestingly,

we find that $E\bar{E}$ rates go much steeper with non-employment duration for individuals with just one $E\bar{E}E$ observation than observed for the full sample: the probit-predicted transition rate is 50% higher, instead of 18%, after 6 months of non-employment.

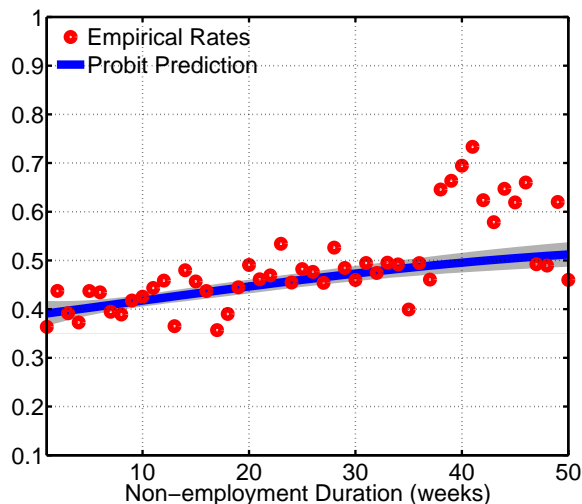


Figure 2: Empirical rates and predicted probabilities of exiting employment within a year. Note: The data are from the 1996 and 2001 SIPP panels for non-recalled workers. The predicted probabilities are the probit-predicted values with all regressors, except for the quartic polynomial of non-employment duration, evaluated at their sample mean. The shaded area represents the 95% confidence interval.

Needless to say, the upward-sloping profile displayed in Figures 2 and 3 could be driven by unobserved heterogeneity since we only control for observable worker characteristics. Although this is beyond the scope of this note,⁸ it is worth mentioning that a number of papers have addressed the question of whether unemployment persistence is mostly driven by unobserved heterogeneity or state dependence. For example, using data on newly high-school graduated young men in the U.S., Heckman and Borjas (1980) find no support for effects on future unemployment of occurrence and duration of past unemployment after controlling for unobserved heterogeneity. In contrast, Arulampalam et al. (2000) and Böheim and Taylor (2002) do find strong evidence of state and duration dependence using data from the British Household Panel Survey.

The left panel of figure 4 shows that the predicted separation rates for recalled workers are less sensitive to the duration of the previous non-employment spells. Furthermore, the right panel displays these duration profiles for young and prime-age workers, with sizable differences in levels across age groups.

⁸In work not shown in this article, we estimate a Probit model as well as a linear probability model with and without fixed effects for the subsample of individuals with more than one observation. We find no appreciable differences between the duration profiles of the $E\bar{E}$ rates predicted from these models.

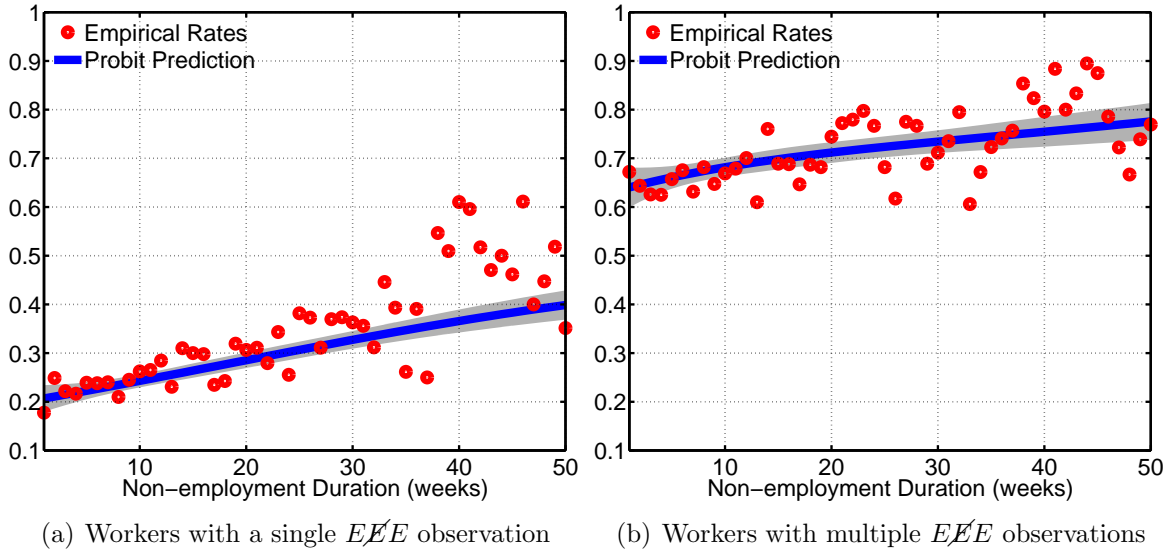


Figure 3: Empirical rates and predicted probabilities of exiting employment within a year, for different subsamples.

Note: The data are from the 1996 and 2001 SIPP panels for non-recalled workers. The predicted probabilities are the probit-predicted values with all regressors, except for the quartic polynomial of non-employment duration, evaluated at their sample mean. The shaded area represents the 95% confidence interval.

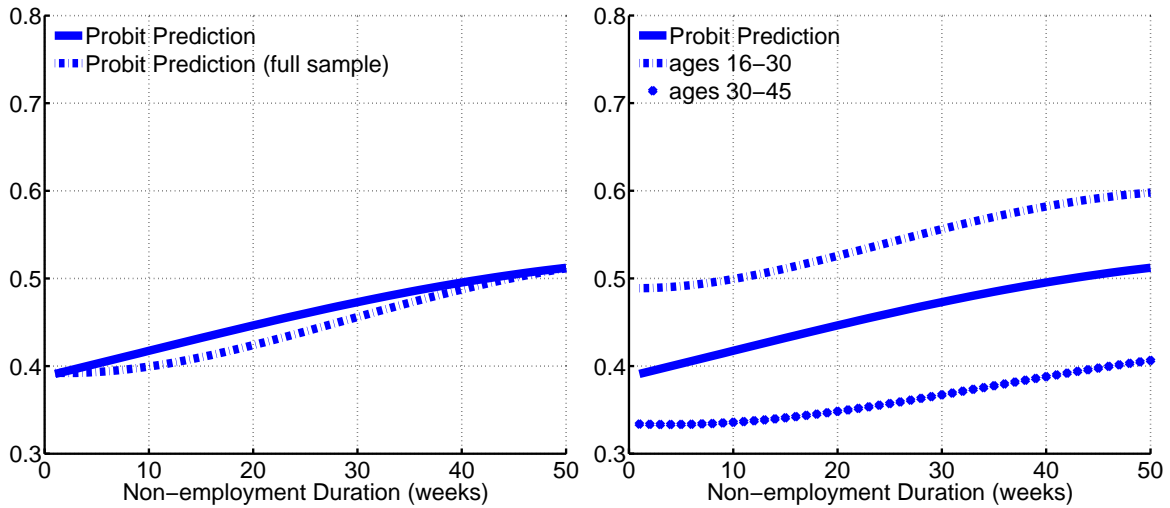


Figure 4: Predicted probabilities of leaving employment within 12 months.

Note: The data are from the 1996 and 2001 SIPP panels. The predicted probabilities are the probit-predicted values with all regressors, except for the quartic polynomial of non-employment duration, evaluated at their sample mean. All values refer to non-recalled workers, unless indicated otherwise.

3.3 Wage Differences Between Stayers and Non-Stayers

We now look at whether the gap in starting wages between stayers and non-stayers reported in Table 2 is statistically significant after controlling for observable worker characteristics.

We regress log wages on the same set of co-variables as above and a dummy which equals 1 if the worker is a stayer. The results of the Mincerian regression are reported in Table 4. The sample is restricted to non-recalled workers. We obtain a log wage difference between stayers and non-stayers equal to 0.132.⁹ Put differently, starting wages in matches that last longer are 14% higher. This estimate hardly rises when analyzing the whole sample, including the rehired workers. When further reducing the sample to prime-age workers, the wage gap does not significantly vary, and it goes down to 0.128 when looking at workers younger than 30 year old. In all cases, the dummy estimate is statistically significant at 1%.

3.4 Cyclicalities of $E\mathcal{E}$ Rates

We turn to investigate the cyclical patterns of the $E\mathcal{E}$ transition rates. We compute the empirical exit rates from employment within the first year at each month a reemployment event occurs. Because the discontinuity in the SIPP data between panels does not allow us to construct continuous time series for the $E\mathcal{E}$ rate, we perform the analysis for each panel separately. Because these time windows are arguably short, we work with monthly data. We use the seasonally adjusted unemployment rate reported by the *Bureau of Labor Statistics* (BLS) as the business cycle indicator.¹⁰

In Figure 5, we present the cyclical components of $E\mathcal{E}$ and unemployment rates, for the four SIPP panels. We construct these figures by removing the trends of the log of the rates using a Hodrick-Prescott filter with parameter 14400.

It is apparent for the four panels that $E\mathcal{E}$ rates are much more volatile than the unemployment rate. Indeed, the volatility of the $E\mathcal{E}$ rate, measured as the standard deviation of the detrended series, seems to somewhat increase over time. Moreover, these transition rates seem to be acyclical or weakly procyclical, in fair accordance with the estimate of our Probit regression reported in Table 4.¹¹ Table 5 confirms these observations. When comparing the earlier time period (average unemployment of 4.9%) with the latter one (great recession, with 8.8% unemployment), the volatility of the $E\mathcal{E}$ rates increased from 0.106 to 0.150, whereas the volatility of unemployment also increased from 0.025 to 0.083. The table also reports that the autocorrelation of the unemployment rate is higher than the autocorrelation of the $E\mathcal{E}$ rate. Finally, the correlation between $E\mathcal{E}$ and unemployment rates is small and negative, with some differences across the considered time periods. These transition rates

⁹When restricting the sample to individuals who separate only once within the panel time window, this estimate is 0.130, and also statistically significant at 1%.

¹⁰The time series of $E\mathcal{E}$ transition rates does not exhibit a seasonal pattern.

¹¹This estimate is not statistically significant at 10% either when considering only individuals with one observation.

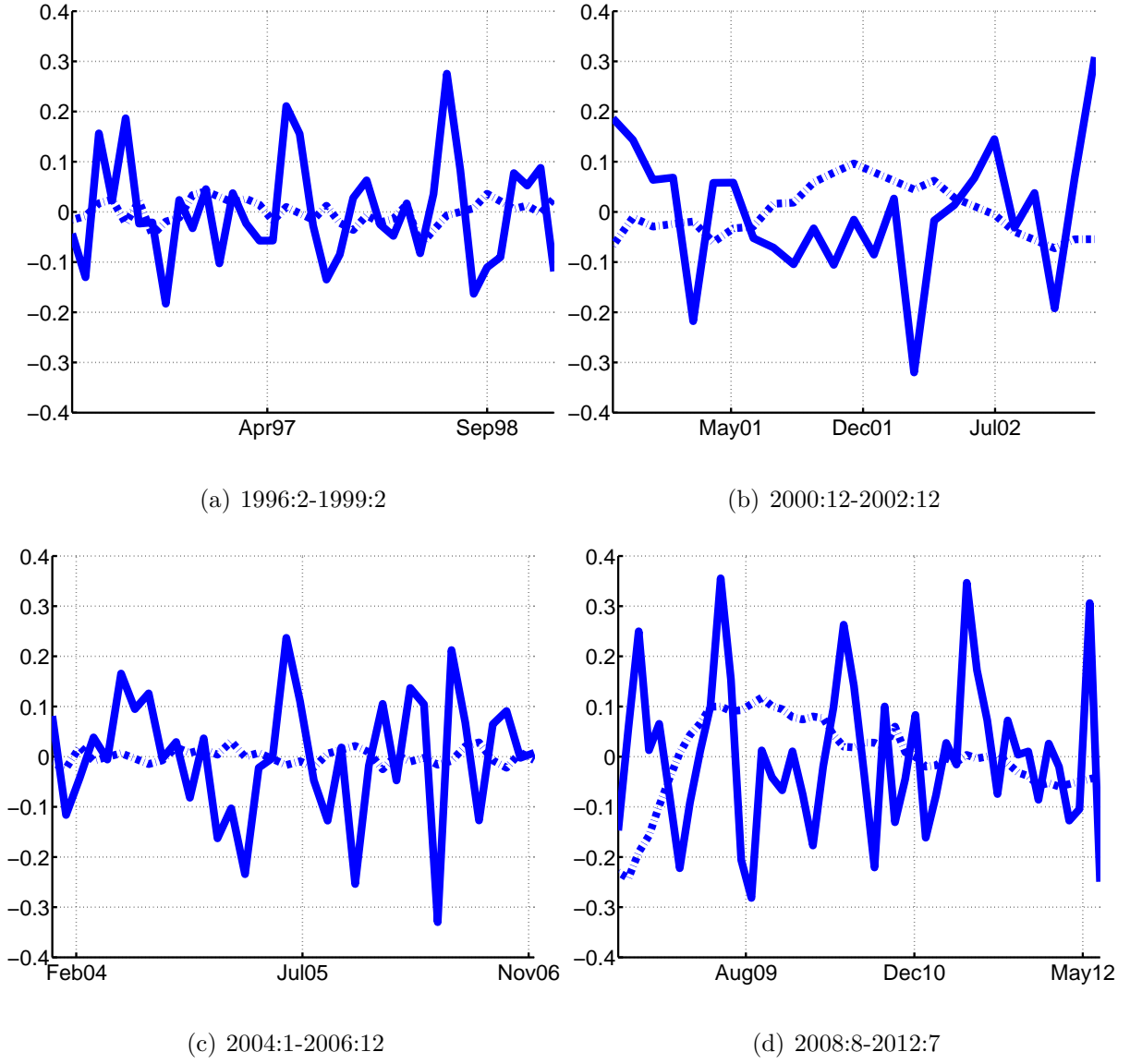


Figure 5: Cyclical component of $E\mathcal{E}$ and national unemployment rates.
Note: The data are from the SIPP panels ($E\mathcal{E}$ rate -solid line-) and from the BLS (unemployment rate -dashed line-). Both $E\mathcal{E}$ and unemployment rates are logged and filtered using a Hodrick-Prescott filter, with parameter 14400.

are acyclical in the first and fourth panels and weakly procyclical in the second and third panels. We explore further the relationship between the business cycle and $E\mathcal{E}$ transition rates by computing the cross-correlation between unemployment and the separation rate at different leads and lags. However, as Figure 6 shows, the cross-correlation between the aggregate unemployment rate at time t and the $E\mathcal{E}$ rate at time $t+k$ (where k is the lead/lag) does not show any consistent pattern.

	$E\mathcal{E}$ rate	Unemployment rate (U)
1996 panel (1996:02-1999:02)		
Average (%)	43.9	4.9
Standard deviation	0.106	0.025
Autocorrelation	0.114	0.295
Correlation with U	-0.026	1.000
2001 panel (2000:12-2002:12)		
Average (%)	41.4	5.2
Standard deviation	0.133	0.052
Autocorrelation	0.089	0.873
Correlation with U	-0.361	1.000
2004 panel (2004:01-2006:12)		
Average (%)	42.7	5.1
Standard deviation	0.126	0.015
Autocorrelation	-0.040	0.121
Correlation with U	-0.301	1.000
2008 panel (2008:08-2012:07)		
Average (%)	39.9	8.8
Standard deviation	0.150	0.083
Autocorrelation	0.158	0.962
Correlation with U	-0.070	1.000

Table 5: Business cycle statistics for $E\mathcal{E}$ and national unemployment rates.

Note: The data are from the 1996 and 2001 SIPP panels ($E\mathcal{E}$ rate) and from the BLS (unemployment rate). Both $E\mathcal{E}$ and unemployment rates are logged and filtered using a Hodrick-Prescott filter, with parameter 14400.

4 Conclusions

We contribute to the literature on worker turnover by uncovering new facts for the U.S. economy. We find that new matches are typically short lived, and estimate the separation rates within a year after reemployment to be above 40%. These transition rates from employment into non-employment within the first year after reemployment are widely heterogeneous across different population groups, are related to duration of previous non-working spells, and are acyclical as well as more volatile than unemployment rate.

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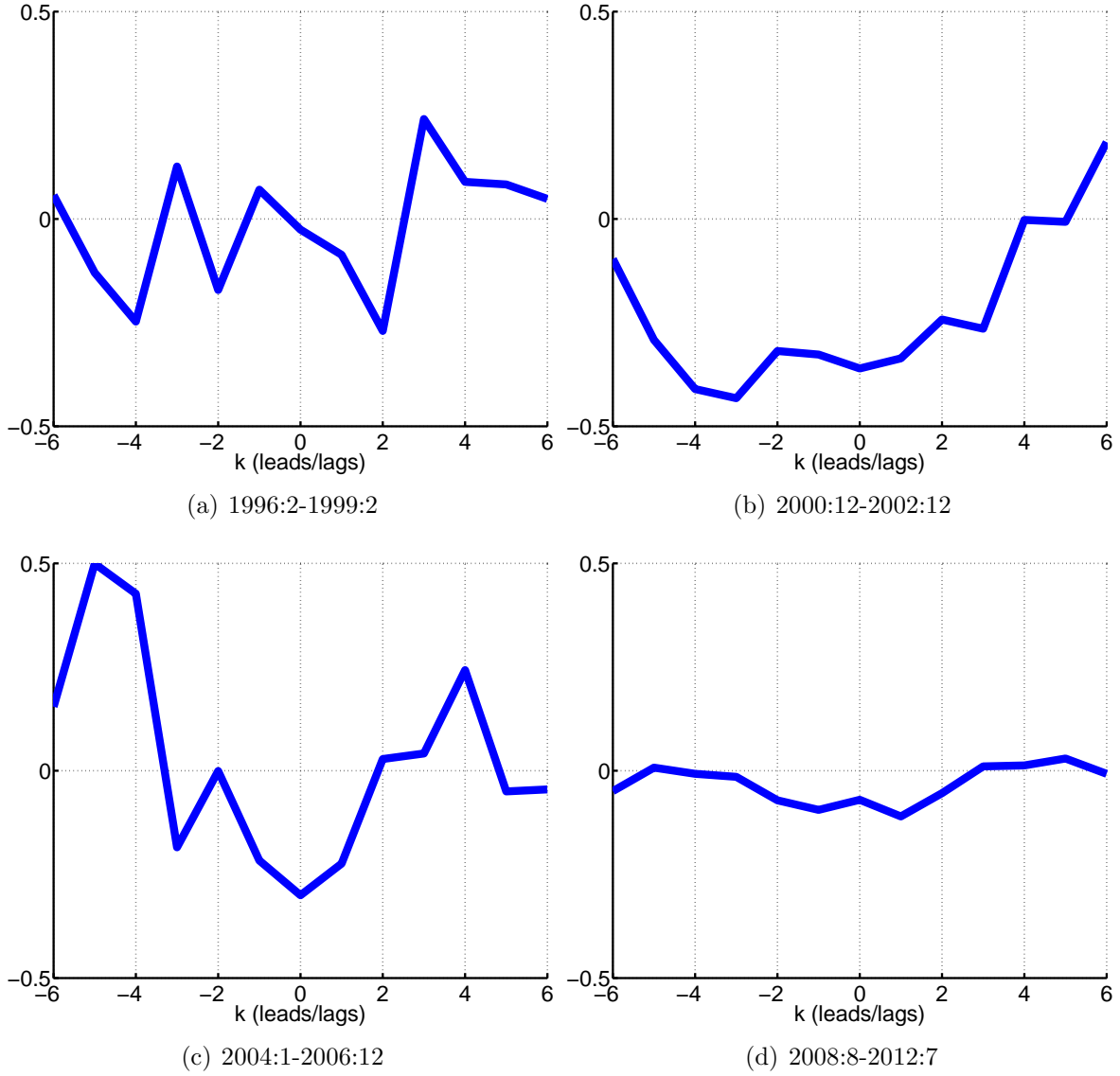


Figure 6: Cross Correlation between the cyclical components of unemployment rate at time t and $E\mathcal{E}$ rate at time $t+k$.

Note: The data are from the 1996 and 2001 SIPP panels ($E\mathcal{E}$ rate) and from the BLS (unemployment rate). Both $E\mathcal{E}$ and unemployment rates are logged and filtered using a Hodrick-Prescott filter, with parameter 14400.

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